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SIMULATING THE EFFECT OF NOISE AND DISTORTIONS ON THE RGB COMPONENT OF COLOR IMAGES

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Abstract. *Color images are used in many sectors such as medical image analysis, content-based image retrieval, remote sensing, and visual quality inspection that have keen interest in color image processing. However, color images are often contaminated with noise, which lowers their visual quality, distorts edge information and complicates automated processing. Therefore, the removal of such noise is often a necessary preprocessing step for color image processing applications. Existing vector filters have problems, in that they are not particularly successful in detecting color distortions in images. They also distort the inherent correlation of the RGB components. In this paper, we investigate whether these shortcomings of the existing vector filters are related or not to differential susceptibility of color components to certain types of noise. The work focuses on (i) estimating the amount of noise in each color component, (ii) examining the characteristics of certain types of noise (Impulse Noise, Gaussian Noise, Speckle/Multiplicative Noise and Poisson Noise), and finally (iii) testing if any of the color components has differential susceptibility to any of the mentioned types of noise. The behavior of each of the noise in the RGB color space is simulated using MATLAB R2014a. From the simulation results, differential susceptibility of color components to noise does not exist.*
Keywords: RGB, Impulse, Gaussian, Multiplicative, Speckle, Poisson, Vector filters

1. **Introduction.** In the electronic industry, color coding of resistors makes identification of electrical gadgets easy by analyzing their color combination. Among other things, this assessment of color information is feasible because color images contain high information level in relation to gray-level images. The information allows color image processing to

succeed in areas where classical gray-level image processing dominates. The confidence level for various techniques can be greatly improved by additional classification markers that color can provide and thereby make the applied procedures simpler and more robust [1].

Also, the assessment of color information plays an important role in an individual object identification. Color is a paramount ingredient in images; it brings out details in an image and makes the image visually pleasing to the human eye. A search strategy is driven by a hierarchical combination of color and model [1,2]. When one is searching for an object that is of model X and of a particular color, the colors of the object facilitate the search process such that one categorizes the objects using the color before the model. If one sees an object of that color, then one quickly finds out its geometry whether it is the object one seeks.

In a sense, color conveys information about an object and this information can be used to further refine the performance of an imaging system [3]. Gray-level images have been used in the past for many applications and exhibitions, but the analysis of gray-level images is inadequate for identifying problems in a particular object. For, gray-level images display only white and black colors and are unable to show some details for better visualization. Hence, it is advisable to use color images for most presentation purposes that display the details of a particular object. The only way to address the gray-level problem is to introduce color.

In color image processing, there are various color models that are in use today. Mostly, the RGB color space is used in hardware oriented applications. The RGB color space is the most convenient model for computer graphics because it mimics the human visual system. In its functioning, the RGB color space represents images by three components that are the primary colors: Red, Green and Blue. Although these are the primary colors in the RGB color space, they are not simply the derivatives of every color. In viewing an object, the human eye characterizes the object in terms of the object's brightness and chromacity. Moreover, the Hue-Saturation-Intensity (HSI) color model and Hue-Saturation-Value (HSV) color model have a human-intuitive advantage in image processing such as color image enhancement, segmentation, fusion, color-based object detection, recognition, traffic signal detection and skin detection but also have some disadvantages [4].

All the same, color images are mostly corrupted through transfer medium, circuitry and faulty sensors, film grains and faulty photon detectors. Likewise, bad working conditions of recording devices subject the image produced to different types of noise corruption. As a result of this, the image quality is reduced, which makes the effectiveness and accuracy of further processing very difficult to perform. However, the noise corruption in grayscale image is simple and easy to remove as compared to color images. As it is generally assumed that noise affects the different components of the vector-value of the color signal, this noise corruption degrades the individual RGB color components [2,5].

Noise in the image must first be removed (preprocessed) to aid further processing in order to improve the perceptual quality, as well as make the image bright and clear for easy identification, and boost high-level-signal processing (e.g., segmentation, clustering and classification). However, to enhance the signal, the image must first be preprocessed [6]. A lot of filters have been suggested for the removal of impulse noise from images (greyscale and color). For example, the nonlinear-ordered- statistics filters have proven to be more successful in impulse noise removal. These filters also perform well in restoring image details and edges [6-8].

The class of ordered statistics filters are categorized into scalar and vector filters [9]. The scalar median filter [9] and all its adaptive counterparts belong to the family of the nonlinear scalar filters. These filters were originally designed for filtering impulse noise from 2D greyscale images [10]. However, they have recently been applied to color images due to their performance. The other categories of filters are the vector filters. For example, the Vector Median Filter (VMF) and all its extensions are developed to solve the problems of the scalar median filters. The scalar median filters were the first filters proposed for noise reduction/removal from color images. These filters are applied in parallel to each color channel separately.

The deficiency of these filters lies in the lack of correlation in the filtering process, which causes a distortion of the inherent correlation between the color channels. The process introduces color artifacts in the image, causing artificial blurring in the image [6]. Furthermore, many scalar median filters have been proposed in literature to improve the performance of the Median Filter (MF) [11], including the Adaptive Median Filter (AMF) [12], Weighted Median Filter (WMF) [13], Center-Weighted Median Filter (CWMF) [14], Alpha-Trimmed Median Filter (ATMF) [15], Switching Median Filters (SMF) [16].

The AMF has two basic stages: the noise detection stage and the noise filtering stage. The noise detection mechanism identifies noisy pixels using the rank ordered absolute difference method on the center pixel and its surrounding pixels. The final stage deals with replacing the noisy pixels detected with the most appropriate value to reduce blurring and over-smoothing. Most of these scalar filters are applied to color to solve the problem of the artificial color generation and blurs introduced into a color image. Though the scalar filters have deficiences, they appear better in performance than their linear counterparts.

Though several scalar median filters were developed to improve their performance, no research has been conducted to find out whether certain color components are differentially more susceptible to noise (one color component is more polluted) than the others. On the other hand, research has been done to prove that the RGB color components have a certain correlation. The outcome of the research motivated further investigation that brought about the design of the Vector Median Filter (VMF) to maintain the correlation among the RGB color components. Additionally, to resolve the problem of artificial color generation, the vector median filter is introduced to treat the color images as a vector field and to process the color pixels as a vector [7].

The VMF works by applying an overlapping window that moves through the entire image until it covers the whole image. At every point of the window, all the pixels in the window are sorted using the reducing ordering metrics. These metrics order the pixels using the sum of the relative difference between each pixel and all its neighbors, which are computed using the Minkowski distance measure. The pixel with the reduced relative distance is selected at the vector median and replaced with the center pixel of that window. This process continues until the overlapping window covers the entire image. The Vector Median does well by suppressing noise and preserving edges. However, it has a shortcoming of replacing some clean pixels in the image with the Vector Median, which distorts the image quality.

This idea of treating the RGB components of a color image as vectors has been extended to the development of several filters. This treatment aims at solving the problem of filtering out a greater percentage of the noise in the image, if not all, and preserving the useful details and edges in the image. Some extensions of the VMF that belong to the uniform filtering category are: Generalized Vector Directional Filter (GVDF) [17], Basic Vector Directional Filter (BVDF) [18], Directional-Distance Filter (DDF) [19], Hybrid Directional Filter (HDF), Adaptive Hybrid Directional Filter (AHDF) [20], Vector Median-Rational Hybrid Filter (VMRHF) [21], and Fuzzy Rational Hybrid Filters [22]. Most of these filters apply the same principle of the VMF but differ in the selection of the vector median value. They employ the angular distance measure in ranking the pixels in the window.

The BVDF applies the angular distance measure in ordering pixels in the window. The Generalized Vector Directional Filter, the DDF, HDF and the AHDF are some sort of hybrid filters that merge two or more filters to improve the performance. Nevertheless, the GVDF combines the BVDF and another scalar filter while the DDF fuses the VMF and BVDF to enhance the filtering process. All these techniques have been implemented but the problem still exists. What is more, this category of filters has a problem detecting color distortions in the individual RGB components of a color image. They also over-smooth the image because they do not have any mechanism for noise detection during the filtering process; hence, they introduce new distortions into the image [8,9].

Another category of vector filters is the Decision Based Median Filters (DBMF) that are built on a robust statistics for resolving the excessive smoothing problem encountered by vector median filters. The DBMFs have a noise detection mechanism that subjects pixel to a series of test. The results of the test determine the behavior of the filter [23]. The operation of this category of filters is based on decision. The most recent decision-based filters are the Decision Based Unsymmetric Trimmed Median Filter (DBUTMF) and the Modified Decision Based Unsymmetric Trimmed Median Filter (MDBUTMF) [24]. The MDBUTMF is an extension of the DBUTMF and outperforms the state-of-the-art switching median filter in high noise intensity regions.

Several shortcomings have been outlined about the family of decision based median filters [7,25,26]. One of the shortcomings concerns blurring of the image when the filters are applied. Also, to overcome the numerous shortcomings of the nonlinear vector filters, a Decision Based Median Filter is proposed in [7]. Another novel category of filters developed to overcome some of the challenges facing the existing filters is the Switching Vector Filter (SVF). Notable among the filters in the SVF category is the Adaptive Rank Weighted Switching Filter (RWASF) [27], which is an extension of the Rank Weighted Switching Filter (RWSF) [27]. The RWASF category of switching filters are developed based on decisions. Their intelligence is based on a set of decisions for efficient operation. Thus, if the decision for a class is not met, then the switching function moves it from that class to another class for testing. The switching function is based on the computation of rank weighted cumulated pixel dissimilarity measures. The unique feature that makes the RWASF achieve better results as compared to the RWSF is the introduction of adaptiveness in its design. The adaptiveness in the design is a modification that helps the filter to tune its parameters depending on the ratio of impulsive noise corrupting the image [27].

Although scalar and vector filters have been proposed to remove noise from color images and preserve all other features (e.g., edges, fine details), none of the recommended filters has achieved this goal. Hence, a filter has to be developed that can completely remove the noise from a color image and preserve its features. To develop an efficient filter that drastically improves the performance of the state-of-the-art filters, differential susceptibility of components of color images and the pattern of each noise should be investigated.

In this paper, we investigate whether the shortcomings of existing vector filters are related to possible existence of differential susceptibility of color components and to noise. The work focuses on (i) estimating the amount of noise in each color component, (ii) examining the characteristics of the following types of Noise (Impulse Noise, Gaussian Noise, Speckle/Multiplicative Noise and Poisson Noise), and (iii) testing whether any of the types of noise mentioned has differential susceptibility of color components. The behavior of each of the noise in the RGB color space is simulated using MATLAB R2014a.

The rest of the work is organized as follows. A brief introduction of the types of noise is given in Section 2. Section 3 outlines a detailed methodology of the investigation. Experimental results of color components susceptibility to noise and the distribution of noise in each color component are outlined in Section 4. Finally, conclusions are presented in Section 5.

2. **Noise in Images.** Basically, noise is any unwanted signal that is introduced into information or data that deteriorates the quality. Also, noise is a process (n) that affects the acquired image (f) and is not part of the scene (initial signal – s). Using the additive noise model, this process can be written as in Equation (1):

$$f(i,j) = x(i,j) + n(i,j) \tag{1}$$

where $f(i,j)$ represents the noisy image; $x(i,j)$ is the original clean image, and $n(i,j)$ is the noise component added to the image.

Digital image noise may come from various sources. For example, the acquisition process for digital images converts optical signals into electrical signals and then into digital signals; this acquisition process is one of the processes by which noise is introduced into digital images. Each step in the conversion process experiences fluctuations, which are caused by natural phenomena, and each of these steps adds a random value to the resulting intensity of a given pixel [28,29]. This study considers Impulse Noise, Gaussian Noise, Speckle/Multiplicative Noise and Poisson Noise for the investigation.

Impulse Noise is one of the commonest unwanted signals or information that degrades the quality of a picture or image, and it is mostly caused by faulty circuitry or transmission error. Usually, Impulse Noise in images replaces the clean pixel values with some arbitrary values equal to or near the maximum or minimum of the allowable dynamic range. For 8-bit images, Impulse Noise often corresponds with a fixed value near 0 or 255. The Probability Density Function of impulse noise is given by:

$$p(z) = \begin{cases} P_a & \text{for } z = a \\ P_b & \text{for } z = b \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

The probability density function describes the distribution of the impulse noise particles in the image [28,29], where "a" and "b" are the pixels values in the image.

Gaussian Noise is an immeasurably recognized amount of unexplained variation of unwanted signal added to a sample. It is a statistically distributed type of noise that will also yield the Probability Density Function (PDF) equal to that of the normal distribution, which can also be called the Gaussian distribution. The PDF of the Gaussian Noise is:

$$P(z) = \frac{1}{\sqrt{2\pi\sigma}} e^{-(z-\mu)^2/2\sigma^2} \tag{3}$$

where z represents gray level, μ is the mean of the average value of z, and σ is the standard deviation of z. The standard deviation square (σ^2) is the variance of z [29].

3. **Methodology of the Study.** The paper tries to mimic situations of real world natural process of noise corrupting an image. Thus, the noise is injected into the entire color image using Matlab function *Imnoise*, which mimics the natural processes for the corruption of images. Then after the noise is injected to the image, the original image and the noisy image are separated into the RGB channels.

The Mean Square Error of each component is computed. These results describe which component deviates widely from its original counterpart, meaning the greater the deviation the more its susceptibility to that particular noise than the other color channels. Figure 1 shows a pictorial representation of the process.

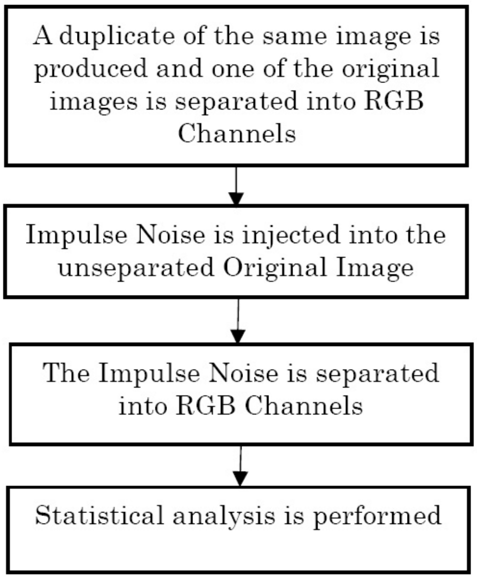


FIGURE 1. A flowchart showing the breakdown of stages of the noise measurement in the RGB channels of the color image

4. **Experimental Analysis.** The simulation to detect the effect of noise used four images: one artificial image of circles (Figure 3) and three real world images, namely, Lena (Figure 2), Mandrill (Figure 4), and Barbara (Figure 5). The simulation was performed on these images to detect the effect of noise on the individual components and the trend of the various image noise.

The real-life images were chosen because of both their popularity in image processing and the distribution of the various colors in the images. On the other hand, the image of circles or balls was chosen to verify whether the noise depended on the spread of the image pixel intensity or on other factors to pollute a particular color component. Below are the images, which were downloaded from the Internet, for the simulation:

FIGURE 2. Lena image [27]

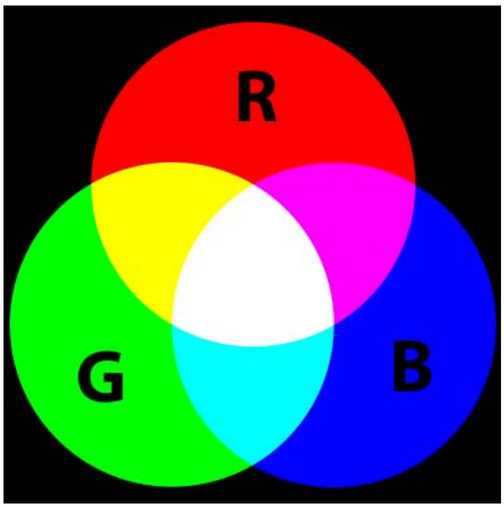


FIGURE 3. Color image of balls [4]

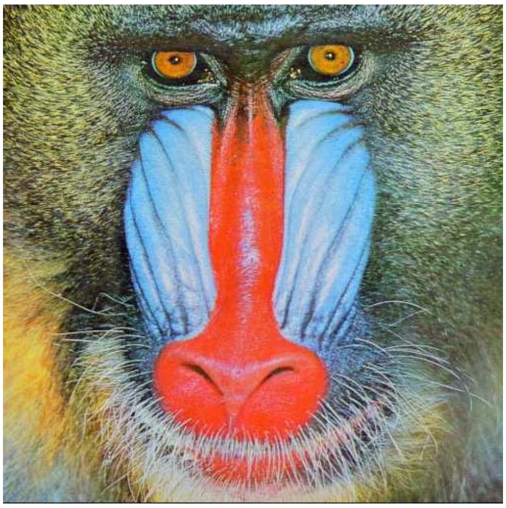


FIGURE 4. Mandrill image [17]

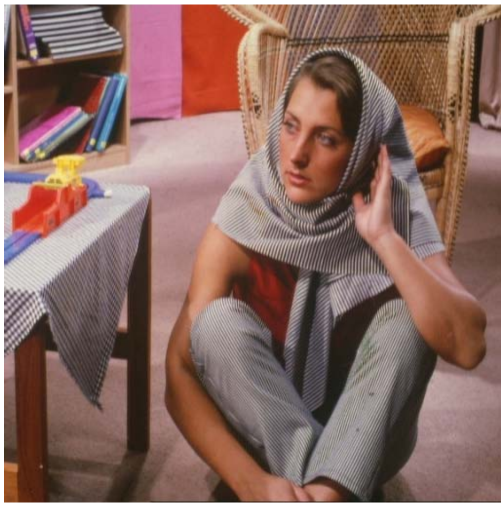
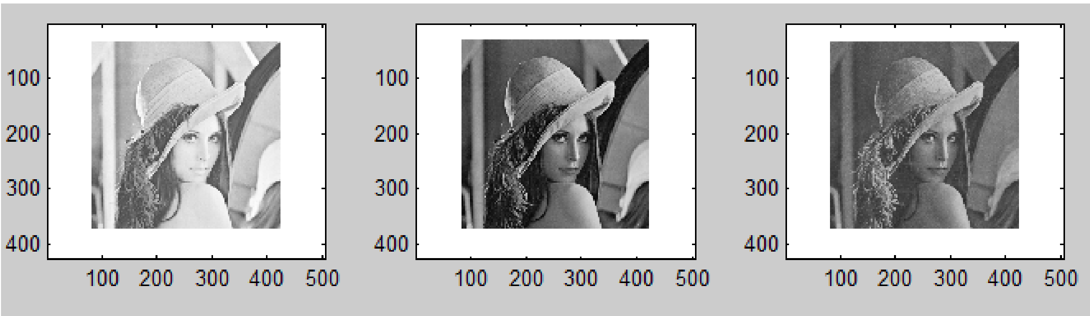
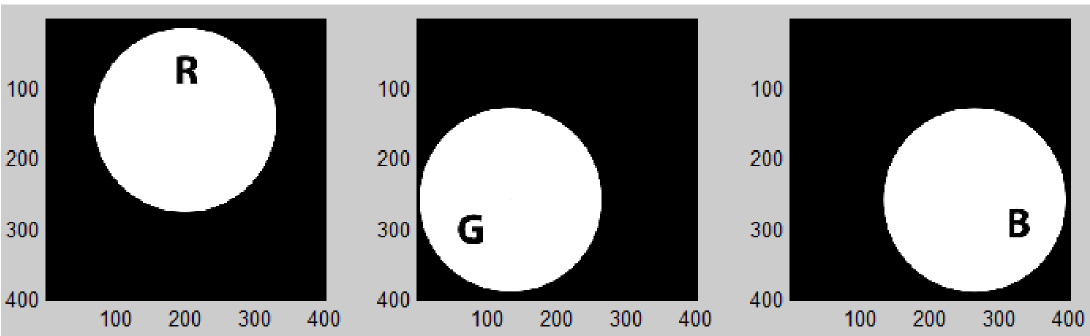


FIGURE 5. Barbara image [30]



Red Green Blue

FIGURE 6. RGB component of the image Lena

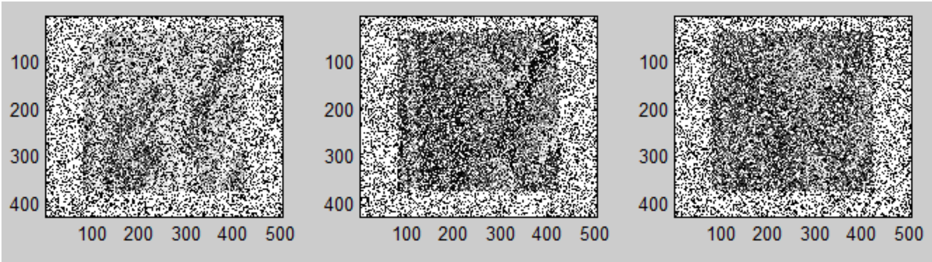


Red Green Blue

FIGURE 7. RGB component of the image circles

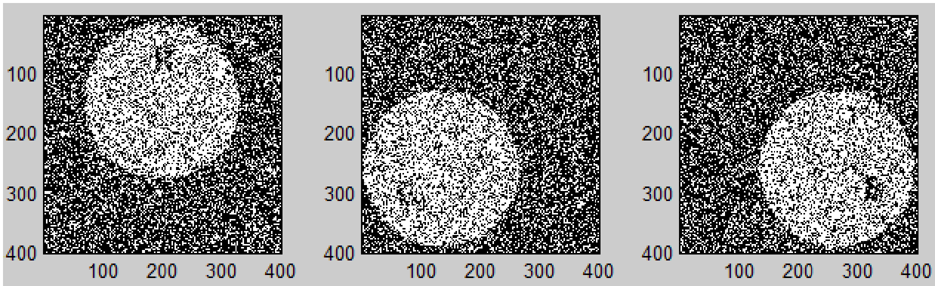
4.1. **Subjective analysis.** In the subjective analysis, the noisy images are separated into their individual 2D RGB channels and shown with the noise pollution and the effect of noise on each color model/space. This process is a visual analysis to find a color component which is more polluted. The visual representation of each color channel tells which regions are more polluted. The effect of the noise pollution impairs the brightness as well as the image quality. The process was carried out on all the images, but just two out of the four are chosen for the purpose of demonstration.

4.1.1. *Results of Impulse Noise.*



Red Green Blue

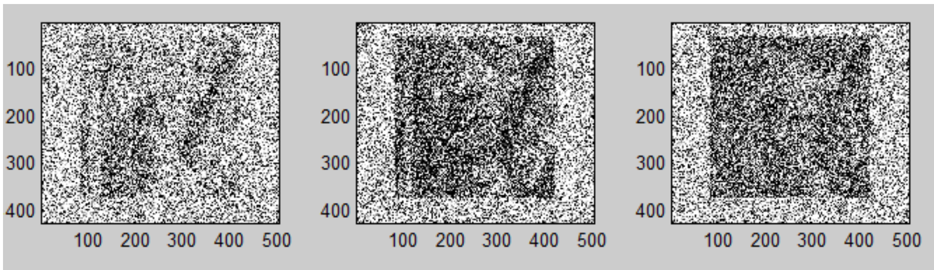
FIGURE 8. 60% pollution of Impulse Noise on the separate RGB color component



Red Green Blue

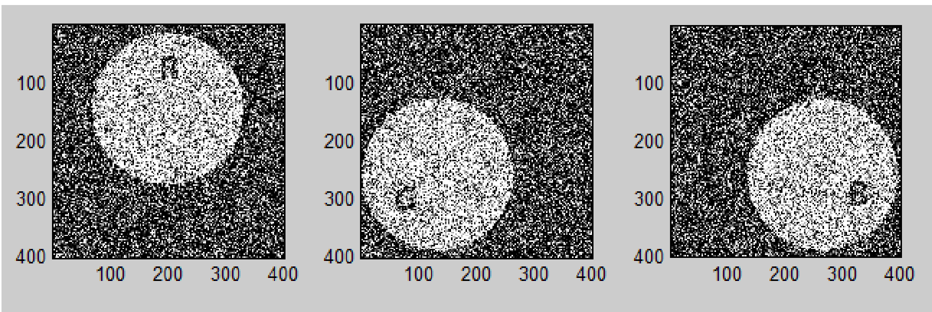
FIGURE 9. 60% pollution of Impulse Noise on the separate RGB color component

4.1.2. *Results of Gaussian Noise.*



Red Green Blue

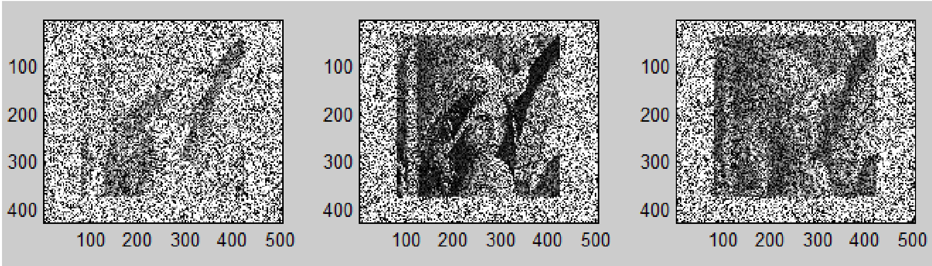
FIGURE 10. 60% pollution of Gaussian Noise on the separate RGB color component



Red Green Blue

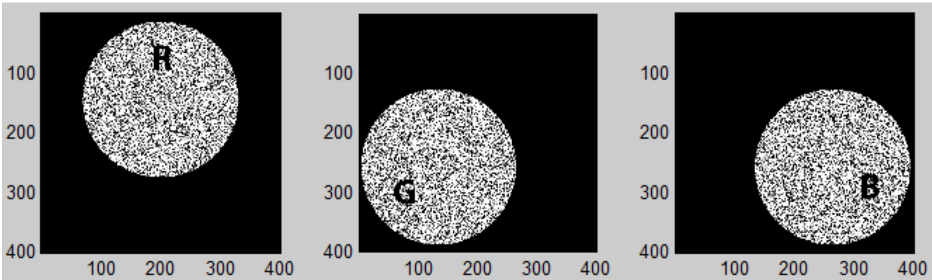
FIGURE 11. 60% pollution of Gaussian Noise on the separate RGB color component

4.1.3. *Results of Speckle/Multiplicative Noise.*



Red Green Blue

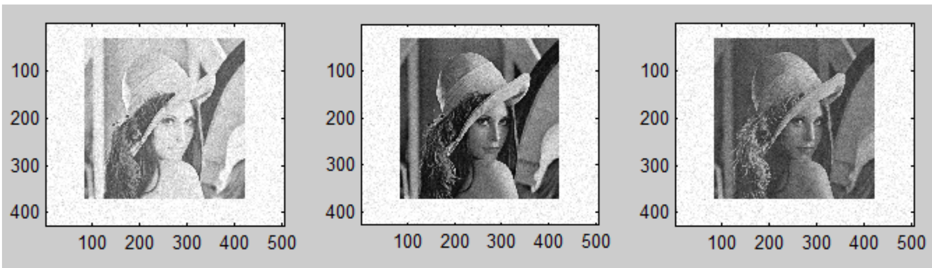
FIGURE 12. 60% pollution of Multiplicative/Speckle Noise on the separate RGB color component



Red Green Blue

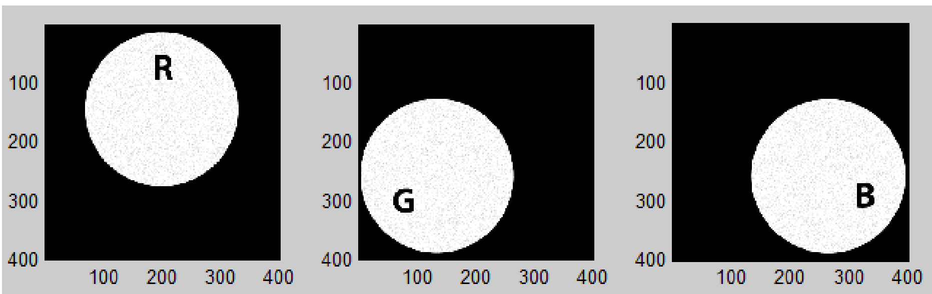
FIGURE 13. 60% pollution of Multiplicative/Speckle Noise on the separate RGB color component

4.1.4. *Result of Poisson Noise.*



Red Green Blue

FIGURE 14. Pollution of Poisson Noise on the separate RGB color component



Red Green Blue

FIGURE 15. Pollution of Poisson Noise on the separate RGB color component

Figures 8-15 give the results of the subjective analysis of the RGB color space. The images are injected with the different, specified types of noise. The results do not give a conclusive indication as to which color channel is more susceptible to noise. The subjective analysis in this research is not able to distinguish between the pattern of noise distribution of each channel and the behavior of the noise in each channel. The visual representation does not also specify which region of the image is more polluted by noise. Generally, it has been stated in literature that the human visual system is not able to measure the amount of noise in an image as well as point out the regions that are most corrupted in an image. Due to the deficiencies encountered by the subjective analysis, this research further employs the objective analysis (a statistical analysis, e.g., MSE) to establish concrete results and to make strong conclusions.

4.2. **Objective analysis.** First, we performed a Null Hypothesis analysis of the simulation data. The focus was to determine which color is susceptible in a particular type of noise. There are three color components (i.e., blue, green, and red) at six levels (10%, 20%, 30%, 40%, 50% and 60%) of noise. At each level of a particular color component, errors are computed by deducting the pixel values of the original image color from those of the corresponding noisy image. Here, the result will be pixel values of which color component deviates most widely from their corresponding original values.

Thus, for each type of noise, three different color components (at six levels each) were tested to determine whether the average amounts of absolute deviations are statistically significant or not. We assumed that for each type of noise, the absolute deviations follow a normal distribution and that their population standard deviations are equal. Our interest is to test the research hypothesis that the average absolute deviation in a particular color is greater than the average absolute deviation of the other color using a two independent sample t-test. Since there are three color components (at six levels of corruption), the appropriate hypotheses to be tested are: H_0: Blue – Green $= 0$ vs H_1: Blue – Green $\neq 0$; H_0: Blue – Red $= 0$ vs H_1: Blue – Red $\neq 0$; and H_0: Green – Red $= 0$ vs H_1: Green – Red $\neq 0$. The MINITAB statistical software was used to do the analysis.

In the analysis table, we reported the following terms at each level of color components: D (which is the difference between the two particular color components in the hypothesis), t-statistics, the p-value (which enables us to make decision on the hypothesis), and the conclusion. If the value of D is positive and the p-value is less than $\alpha = 0.05$; then we reject the H_0. Thus, we conclude that the average absolute deviation is more in the first color as compared to the second color. This means that the first color component is more susceptible in that particular type of noise than the second color component. However, if the p-value is greater than $\alpha = 0.05$; then we fail to reject the H_0. This means that the color components have the same level of susceptibility. Similarly, if the value of D is negative and the p-value is less than $\alpha = 0.05$; then we reject the H_0. Thus, we conclude that the average absolute deviation is more in the second color as compared to the first color. This means that the second color component is more susceptible in that particular type of noise.

Table 1 shows the result of the Null Hypothesis analysis of data obtained by taking errors from the Lena image, which had been corrupted with Impulse Noise. The results indicate that both the red and green color components are more susceptible than the blue color component. However, tests conducted on the other images corrupted with Impulse Noise gave different results. The results obtained from the images corrupted with other noise types were similarly inconsistent.

Secondly, we employed the Mean Square Error (MSE) estimator. The Mean Square Error is arguably one of the most robust methods for evaluating the performance of the

TABLE 1. Analysis of Impulse Noise on the blue, red and green channels of the Lena image

Impulse					
Color Groups	**Level (%)**	**Difference**	***t*-stat.**	***p*-value**	**Conclusion**
Blue vrs Green H_0: *Blue = Green*	10	0.18	0.64	0.52	Do not reject H_0. Deviation is not significantly different in both green and blue colors.
	20	29.16	86.57	0.00	Reject H_0. Deviation is more in the blue color.
	30	−0.93	−2.03	0.04	Reject H_0. Deviation is more in the green color.
	40	0.03	0.06	0.95	Do not reject H_0. Deviation is not significantly different in both green and blue colors.
	50	0.39	0.74	0.46	Do not reject H_0. Deviation is not significantly different in both green and blue colors.
	60	−13.1	−24.1	0.00	Reject H_0. Deviation is more in the green color.

TABLE 2. Analysis of Impulse Noise on the blue and red channels of the Lena image

Impulse					
Color Groups	**Level (%)**	**Difference**	***t*-stat.**	***p*-value**	**Conclusion**
Blue vrs Red H_0: *Blue = Red*	10	−0.31	−1.12	0.26	Do not reject H_0. Deviation is not significantly different in both blue and red colors.
	20	29.09	88.9	0.00	Reject H_0. Deviation is more in the blue color.
	30	−0.62	−1.38	0.16	Do not reject H_0. Deviation is not significantly different in both blue and red colors.
	40	−0.98	−1.98	0.04	Reject H_0. Deviation is more in the red color.
	50	0.07	0.15	0.88	Do not reject H_0. Deviation is not significantly different in both blue and red colors.
	60	−12.9	−24.67	0.00	Reject H_0. Deviation is more in the red color.

quantities (in terms of their magnitude or weights). The MSE is a useful tool for measuring precision and accuracy of the distances between two quantities in statistical estimation.

$$MSE = \frac{1}{MN}\sum_{j=1}^{M}\sum_{i=1}^{N}(G(i,j) - F(i,j))^2 \tag{4}$$

The terms used are defined as follows: M and N are the total number of pixels in the column and row of the image, G denotes the noise image and F denotes the filtered image. Figures 8-15 show some of the results of graphical presentations of the average effect of noise on the color components in the images by evaluating different percentages of noise in each component. From the graphs, the blue component gets more polluted with Impulse

Noise than the rest of the color components followed by the green component in some cases and the red component too in few cases. For Gaussian Noise the intensity of the noise variation is very negligible. In most of the cases, the spread of the noise is uniform in the color components. The Speckle Noise is also evenly distributed in the case of the green and red components in most cases, but the red component is more susceptible to Speckle Noise. This noise affects the red component more than the other components in most of the cases.

TABLE 3. Analysis of Impulse Noise on the green and red channels of the Lena image

Impulse					
Color Groups	**Level (%)**	**Difference**	***t*-stat.**	***p*-value**	**Conclusion**
Green vrs Red H_0: *Green = Red*	10	−0.49	−1.8	0.07	Do not reject H_0. Deviation is not significantly different in both green and red colors.
	20	−0.06	−0.18	0.86	Do not reject H_0. Deviation is not significantly different in both green and red colors.
	30	0.32	0.74	0.47	Do not reject H_0. Deviation is not significantly different in both green and red colors.
	40	−1.01	−2.1	0.03	Reject H_0. Deviation is more in the red color.
	50	−0.32	−0.64	0.52	Do not reject H_0. Deviation is not significantly different in both green and red colors.
	60	0.16	0.32	0.75	Do not reject H_0. Deviation is not significantly different in both green and red colors.

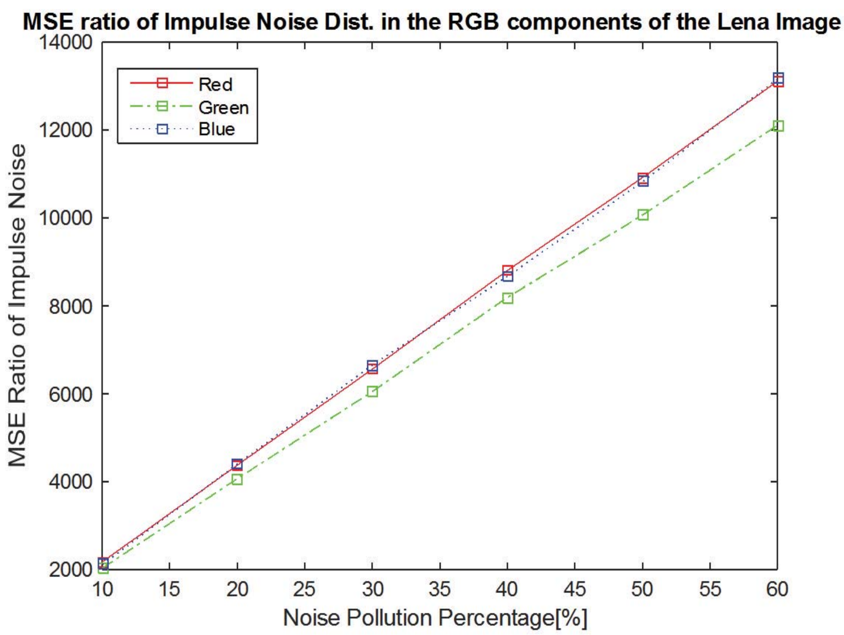


FIGURE 16. MSE ratio of Impulse Noise distribution in the RGB components of the Lena image

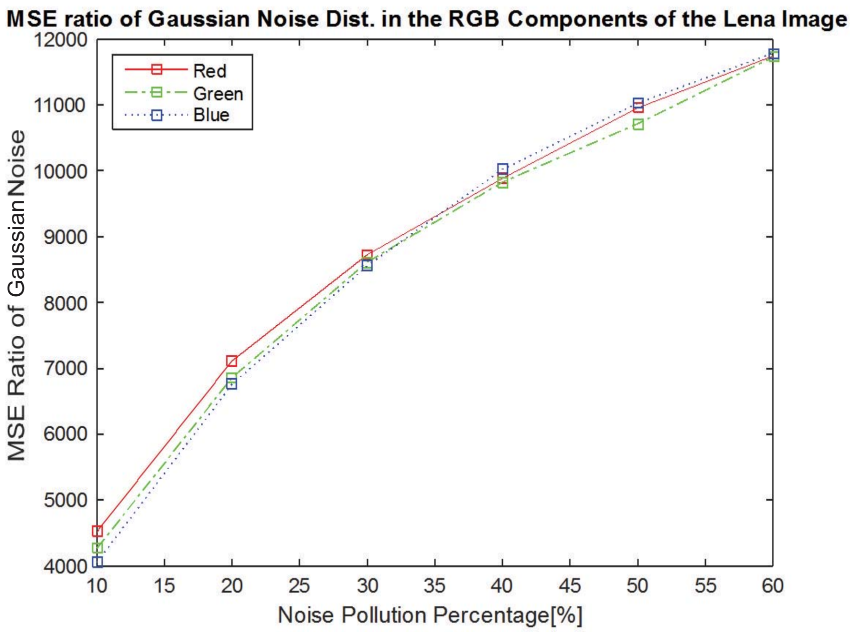


FIGURE 17. MSE ratio of Gaussian Noise distribution in the RGB components of the Lena image

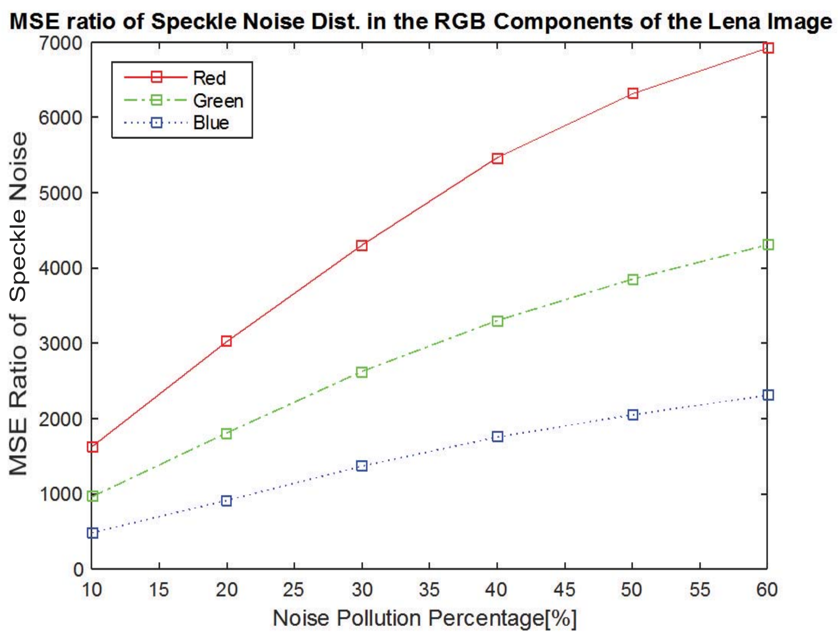


FIGURE 18. MSE ratio of Speckle Noise distribution in the RGB components of the Lena image

4.3. **Discussion of results.** A lot of algorithms have been developed to suppress noise and distortions in color images, but no research has been conducted to quantify the amount of noise that pollutes each individual color component in the RGB color space. This research was conducted to investigate types of image noise, their characteristics and the pattern of their distribution in each color RGB component. The work focused on the intensity of noise pollution on color images; hence, the research adopted both the subjective and objective analyses for evaluating the effect of the noise pollution. In the subjective analysis the induced color image is separated in the different components and the image is analyzed visually to verify which of the color components is much polluted. The results produced a bias analysis since some image components appear more polluted than others visually, but a quantitative analysis proved the opposite.

In the objective analysis two independent sample t-test is used to determine if any particular color component is particularly susceptible to any of the types of noise. Also, the Mean Squared Error estimations applied was to determine which of the color components has the highest rate of pollution for each type of noise. Four different images, namely, Lena, circles, Mandrill and Barbara images were used in these statistical analyses. All the images appeared to have different proportions of noise distributions in the Red, Green and Blue colors. The objective results did not show any consistency in the results that would suggest that any particular color component is more susceptible to any particular type of noise. Thus, all indications show that the distribution of color intensities in a color image has an influence on the spread of noise in the color components of the image.

From the simulation results and analysis shown in Figures 16-18 and Tables 1-3, the differential susceptibility of certain color components to certain types of noise does not exist, which is shown by the inconsistencies of the results. The inconsistencies suggest that the problem lies elsewhere. Based on the findings of this research we conclude that no filter should be developed to target a particular color channel for noise reduction because the noise spread in a color is not consistent. Hence, the search for an alternative technique to improve on the performance of the traditional vector median filtering method should not target any particular color channel. Rather, more focus should be placed on developing a hybrid to take care of the inconsistent pattern of the noise spread.

5. **Conclusions.** This research focused on the effects of image noise, their characteristics and distribution in each color component in the RGB color space. To deal with the intensity of noise pollution on colored images, the research adopted both the subjective and objective analyses for evaluating the effect of the noise pollution. In the subjective analysis, the induced color image was separated into the different components; the image was analyzed visually to verify if one of the color components was more polluted than the other or they were equally polluted. The result of the subjective analysis is not so convincing because the human eye is a bias analyzer of visual quality. Yet, it appears some color components are more polluted than others in some cases from the simulation. In order to provide a more solid and convincing results, the objective analysis is employed. Thus, the Null Hypothesis test as well as Mean Squared Error estimator were used to measure which of the color components has the highest rate of pollution and by which type of noise. From the simulation results and analysis, differential susceptibility of certain color components to noise does not exist, which is shown by the inconsistencies of the results. Also, the amount of noise in each component varies from image to image. The varying behavior of the noise in different images suggests that the spread of noise in an image depends on the intensities of the image. Therefore, this work may serve as a good road map to the development of filters to remove or suppress noise in color images while preserving the image quality.

REFERENCES

[1] W. Chen, Y. Q. Shi and G. Xuan, Identifying computer graphics using HSV color model and statistical moments of characteristic functions, *2007 IEEE International Conference on Multimedia and Expo*, pp.1123-1126, 2007.

[2] B. Mahdian and S. Saic, A bibliography on blind methods for identifying image forgery, *Image Commun.*, vol.25, pp.389-399, 2010.

[3] Y.-T. Kim, Contrast enhancement using brightness preserving bi-histogram equalization, *IEEE Trans. Consumer Electronics*, vol.43, pp.1-8, 1997.

[4] M. Loesdau, S. Chabrier and A. Gabillon, Hue and saturation in the RGB color space, *Proc. of the 6th International Conference on Image and Signal Processing, ICISP*, Cherbourg, France, pp.203-212, 2014.

[5] P. Y. Abhishek Yadav, *Digital Image Processing*, 2009.

[6] K. O. Boateng, B. W. Asubam and D. S. Laar, Improving the effectiveness of the median filter, *International Journal of Electrical Communication Engineering*, vol.5, pp.85-97, 2012.

[7] S. Esakkirajan, T. Veerakumar, A. N. Subramanyam and C. H. Premchand, Removal of high density salt and pepper noise through modified decision based unsymmetric trimmed median filter, *IEEE Signal Processing Letters*, vol.18, pp.287-290, 2011.

[8] S. Morillas and V. Gregori, Robustifying vector median filter, *Sensors*, vol.11, pp.8115-8126, 2011.

[9] H. J. Trussell, E. Saber and M. Vrhel, Color image processing: Basics and special issue overview, *IEEE Signal Processing Magazine*, vol.22, pp.12-22, 2005.

[10] D. Ghimire and J. Lee, Nonlinear transfer function-based local approach for color image enhancement, *IEEE Trans. Consumer Electronics*, vol.57, pp.858-865, 2011.

[11] Y. Zhu and C. Huang, An improved median filtering algorithm for image noise reduction, *Physics Procedia*, vol.25, pp.609-616, 2012.

[12] V. R. Vijaykumar and P. Jothibasu, Decision based adaptive median filter to remove blotches, scratches, streaks, stripes and impulse noise in images, *2010 IEEE International Conference on Image Processing*, pp.117-120, 2010.

[13] Q. Zhang, L. Xu and J. Jia, 100+ times faster weighted median filter (WMF), *2014 IEEE Conference on Computer Vision and Pattern Recognition*, pp.2830-2837, 2014.

[14] S. J. Ko and Y. H. Lee, Center weighted median filters and their applications to image enhancement, *IEEE Trans. Circuits and Systems*, vol.38, pp.984-993, 1991.

[15] J. Bednar and T. Watt, Alpha-trimmed means and their relationship to median filters, *IEEE Trans. Acoustics, Speech, and Signal Processing*, vol.32, pp.145-153, 1984.

[16] C. Yuan and Y. Li, Switching median and morphological filter for impulse noise removal from digital images, *Optik – International Journal for Light and Electron Optics*, vol.126, pp.1598-1601, 2015.

[17] P. E. Trahanias, D. Karakos and A. N. Venetsanopoulos, Directional processing of color images: Theory and experimental results, *IEEE Trans. Image Processing*, vol.5, pp.868-880, 1996.

[18] P. E. Trahanias and A. N. Venetsanopoulos, Vector directional filters – A new class of multichannel image processing filters, *IEEE Trans. Image Processing*, vol.2, pp.528-534, 1993.

[19] L. Jin and D. Li, Improved directional-distance filter, *Frontiers of Mechanical Engineering in China*, vol.3, pp.205-211, 2008.

[20] X. Guo, B. Guo, T. Hu and O. Yang, An adaptive hybrid filtering for removing impulse noise in color images, *Proc. of the 6th International Symposium on Neural Networks*, Wuhan, China, pp.494-501, 2009.

[21] M. Gabbouj and F. A. Cheickh, Vector median-vector directional hybrid filter for color image restoration, *Proc. of EUSIPCO*, vol.92, pp.879-882, 1996.

[22] L. Khriji and M Gabbouj, Rational-based adaptive fuzzy filters, *International Journal of Computational Cognition*, vol.2, pp.113-132, 2004.

[23] J. Zhang, X. Tang, J. Zhang and X. Tang, An algorithm for impulsive noise removal in color images, *Proc. of the 3rd International Conference on Multimedia Technology*, vol.84, pp.1513-1520, 2013.

[24] P. Kaur and M. Kaur, Decision based trimmed adaptive windows median filter, *International Journal of Science and Research*, vol.6, pp.40-43, 2013.

[25] K. Aiswarya, V. Jayaraj and D. Ebenezer, A new and efficient algorithm for the removal of high density salt and pepper noise in images and videos, *The 2nd International Conference on Computer Modeling and Simulation*, pp.409-413, 2010.

[26] V. Jayaraj and D. Ebenezer, A new switching-based median filtering scheme and algorithm for removal of high-density salt and pepper noise in images, *EURASIP J. Adv. Signal Process*, vol.2010, pp.1-11, 2010.

[27] B. Smolka, K. Malik and D. Malik, Adaptive rank weighted switching filter for impulsive noise removal in color images, *Journal of Real-Time Image Processing*, vol.10, pp.289-311, 2015.

[28] B. A. Weyori and K. O. Boateng, Dynamic intelligent mean filter for impulse noise suppression in 2D images, *International Journal of Modern Engineering*, vol.13, pp.60-67, 2013.

[29] A. K. Boyat and B. K. Joshi, A review paper: Noise models in digital image processing, *Signal & Image Processing: An International Journal*, vol.6, pp.63-75, 2015.

[30] B. Zitová and J. Flusser, Image registration methods: A survey, *Image and Vision Computing*, vol.21, pp.977-1000, 2003.